GreenBroker: Optimal Electric Vehicle Park-and-Charge Control via Vehicle-to-Infrastructure Communication

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***Abstract*—The increasing market share of electric vehicles (EVs) makes charging facilities indispensable infrastructure for integrating EVs into the future smart grid. The promising facility called park-and-charge station was recently proposed. Existing studies on park-and-charge station mainly focus on managing the charging distribution of onsite EVs, ignoring the impacts of offsite EVs in the region. In this paper, we fill this gap by leveraging the emerging vehicle-to-infrastructure (V2I) communication technique to manage the charging schedule of both onsite and offsite EVs. Specifically, we design a park-and-charge management system, *GreenBroker*, which allows park-and-charge stations to control the arriving rate by sending real-time prices to EVs via V2I communications, and to control the charging rate via real-time electricity state. We develop a two-timescale stochastic optimization model, maximizing the revenue of park-and-charge stations while ensuring a finite charging delay of EV users. We derive the worst-case charging delay of EVs and show that it provides an $[O(1/V), O(V)]$ tradeoff between the revenue of charging stations and the worst-case delay of EV users. We also demonstrate the efficacy of *GreenBroker* via trace-data simulation.**

I. Introduction

Electric vehicle (EV) is a crucial component in the future intelligent transportation systems (ITS) [4]. Compared with gasoline-powered vehicles, EVs have the potential benefits of a higher power efficiency, a lower carbon emission and a lower powering cost. With these promising benefits, nonetheless, they also introduce a high penetration into the power grid. With the increasing market share of EVs, the integration of EV into smart grid has drawn much attention from both academia and industry. And charging facilities are indispensable infrastructure for such integration [5].

Among various charging facilities [4], [5], [8], a promising facility called park-and-charge station was recently proposed. It allows people to park their EVs at a parking lot while being charged via onsite renewable energy, e.g., solar and wind power. There are quite a few potential application scenarios for this facility, include parking-lot charging at workplace, shopping mall, and airport. Field experiments have been done to explore its feasibility and benefits [3], [12]. Though these experiments provide positive feedback , they mainly focus on managing the charging distribution of onsite EVs and ignore the impacts of offsite EVs.

How to manage the charging of offsite EVs is challenging due to two key reasons. First, there is a lack of reliable control channel between charging stations and EVs. Second, there is a lack of systematic understanding of the trade-off between revenue maximization of park-and-charge stations and guaranteeing the delay for EV users.

In this paper, we cope with these issues by designing *GreenBroker*, a park-and-charge management system to manage the charging of both onsite and offsite EVs. The first key design decision is a reliable control channel between park-and-charge stations and EVs in the region using the emerging vehicle-to-infrastructure (V2I) communication. In this way, *GreenBroker* can control the arriving rate of charging demand by sending the charging prices to EVs, and control the charging rate via real-time electricity generation and trading. Second, we develop a two-timescale stochastic optimization model to maximize the revenue of park-and-charge stations while ensuring a finite charging delay of EV users [11].

Our **main** contributions in this paper are as follows:

• We study the novel problem of joint control of onsite and offsite EVs for park-and-charge stations, and design *GreenBroker*, a park-and-charge management system that builds a control channel between stations and EVs using the emerging V2I communication technique, and adopts a two-timescale stochastic optimization model to maximize the revenue of park-and-charge stations while ensuring finite charging delays of EV users.

• Through theoretical analysis, we show that *GreenBroker* provides a deterministic worst-case charging delay for EV users. It achieves an $[O(1/V), O(V)]$ tradeoff between the time-averaged revenue of park-and-charge stations and the worst-case delay of EV users.

• We evaluate the performance of *GreenBroker* through extensive real-world trace-data simulation.

II. System Description

We consider a set of N EV park-and-charge stations, denoted by $i = 1, 2, \ldots, N$, operating in a discrete-time model. In each station i, a charging point is equipped at every parking spot. And we use j to denote a given EV user. Time is divided into coarse-grained time slots, each of which is of length T. Each coarse-grained time slot is denoted by $t = kT$, where $k = 0, 1, 2, \ldots, K$. Given a coarse-grained time slot t, we further divide it into F fine-grained time slots each of which is of length $\xi = \frac{T}{F}$. These fine-grained time slots are denoted by $\tau = t + 0, t + \xi, \ldots, t + (F - 1)\xi$.

1) V2I-Communication Enabled Park-and-Charge Stations. Figure 1 gives an overview on the operation of park-and-charge stations. Each station is equipped with DSRC-enabled communication devices to communicate with EVs in the nearby region. For every charging station i, its operation strategy is composed of three parts. The first part is the **electricity pricing strategy**. It requires station i to decide a nonnegative charging price (*electricity pricing variables*) $p_i(t)$ at the beginning of each coarse-grained time slot t. After deciding $p_i(t)$, the station i will broadcast the price to all EV users who can arrive at station i by the end of time slot t. We define a price cap p_{max} as the highest charging price.

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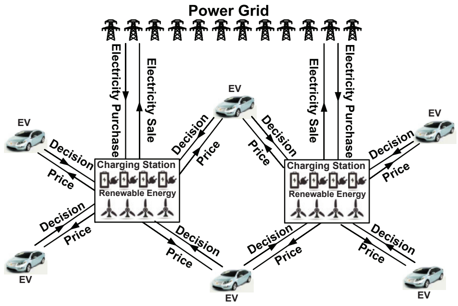


Fig. 1: An overview depicting how charging stations integrate demand response of EV users into operation strategizing.

This cap is to prevent the speculation behavior of charging stations. Then we have:

$$0 \leq p_i(t) \leq p_{max} \qquad \forall\ i \text{ and } t. \tag{1}$$

An EV user j may be close to multiple charging stations and thus receive multiple prices $p_i(t)$s. User j should select the price of *at most* one charging station and transmits back to each charging station.

The second part of operation strategy is **electricity generating and trading strategy** for charging stations. Assume that every station i is equipped with on-site renewable energy generator, e.g., solar panels and wind turbines, and the electricity generated by renewable energy is free [10]. Park-and-charge stations can sell the surplus electricity back to the power grid. They can also purchase electricity from power grid when the renewable energy is insufficient as shown in Figure 1. At the beginning of each fine-grained time slot τ, this strategy requires each station i to determine three *electricity generating and trading variables*: $r_i(\tau)$, the amount of electricity to be generated by renewable source during τ; $E_{Gi}(\tau)$, the amount of electricity to be purchased from the power grid during τ; and $E_{iG}(\tau)$, the amount of electricity to be sold to the power grid during τ.

Because the prediction of renewable energy generation capacity for a short time interval can be very accurate [7], the station i is aware of its renewable energy generation capacity $R_i(\tau)$. Then, we have the constraint on electricity generation at station i in each fine-grained time slot:

$$0 \leq r_i(\tau) \leq R_i(\tau) \qquad \forall\ i \text{ and } \tau. \tag{2}$$

In addition, due to the constraints of hardware and policy, both the purchased and the sold electricity within a fine-grained time slot are also upper bounded, denoted by $E_{Gi}^{\tau-max}$ and $E_{iG}^{\tau-max}$, respectively.

$$0 \leq E_{Gi}(\tau) \leq E_{Gi}^{\tau-max} \qquad \forall\ i \text{ and } \tau, \tag{3}$$

$$0 \leq E_{iG}(\tau) \leq E_{iG}^{\tau-max} \qquad \forall\ i \text{ and } \tau. \tag{4}$$

The third part is **charging demand dropping strategy**. For a charging station i, it makes the dropping decision at the beginning of every coarse-grained slot t to drop an amount of $d_i(t)$ charging demand of EV users so that their the worst-case delay can be guaranteed.

We propose a dedicated *proportional dropping* for EV charging request. This dropping policy leverages the fact that the charging demand of EV users can be segmented. Suppose there are M EVs parked in station i. For each EV j, we denote its charging demand as Cr_j. If station i decides to drop an amount of $d_i(t)$ charging demand in time slot t, a proportional dropping policy will drop an amount of $\frac{Cr_j}{\sum_j Cr_j} d_i(t)$ charging demand. In this way, the charging station prevents the "waiting for nothing" situation. Every EV only suffers a small amount of unserved charging demand while the fairness of all EVs are maintained. The dropping variables are subject to constraint:

$$0 \leq d_i(t) \leq \lambda_{max}^t, \tag{5}$$

where λ_{max}^t is the maximal arrival rate of EV charging demand in a coarse-grained slot t. In addition, we assume that the charging station will pay a total penalty of $p_{max} d_i(t)$ to EV users based on their respective dropped demand.

2) V2I-Communication Enabled EVs. Each EV is also equipped with V2I communication devices for receiving the price and location information from charging stations and responding the charging decisions, e.g., where and how much to charge. For an EV j, a 5-tuple $\{x_j(t), y_j(t), SOC_j(t), D_j(t), E_j\}$ vector is adopted to denote its basic information at the beginning of time slot t, where $\{x_j(t)$ and $y_j(t)\}$ represent the geographic coordinates of j, $SOC_j(t)$ and $D_j(t)$ represent the state of charge and the corresponding driving range of j. E_j is the maximal battery capacity of EV j. We use $\mathcal{N}_j(t)$ to denote the set of charging stations that EV j can arrive by $t+T$. Thus at the beginning of t, EV user j will receive the price $p_i(t)$ from station i.

We use the following *quadratic charging station selection function* to capture all the aforementioned demand response preferences. Given an EV j at the beginning of slot t, we use $Pr_j^i(t)$ to denote the probability that j accepts the price $p_i(t)$ provided by charging station i, and express it as

$$Pr_j^i(t) = \frac{1-\left(\frac{\kappa_p p_i(t)}{\kappa_p p_{max}+\kappa_s(1-SOC_j(t))+\kappa_d(1-\frac{d_{ij}(t)}{D_j(t)})}\right)^2}{|\mathcal{N}_j(t)|}, \tag{6}$$

where $d_{ij}(t)$ is the distance from station i to $\{x_j(t), y_j(t)\}$ and κ_p, κ_s and κ_d are impact factors reflecting the relative importance of price, SOC, and distance on $Pr_j^i(t)$. For every EV j, this function has the following property: $\sum_i^{\mathcal{N}_j(t)} Pr_j^i(t) \leq 1$.

III. Revenue Maximization for Park-And-Charge Facilities: A Stochastic Optimization Model

In this section, we present a stochastic optimization model for the revenue maximization of park-and-charge facilities.

A. Queueing Model for Park-and-Charge Facilities

Given a system of N charging stations owned by the same entity, we use a vector of queues $\mathbf{Q} = \{Q_1, Q_2, \ldots, Q_N\}$ to record the charging demand pending at charging stations. We have $Q_i(0) = 0$ for every i. Since we further divide each coarse-grained time slot $t = kT$ into F fine-grained time slots $\tau = t, t+\xi, \ldots, t+(F-1)\xi$, we first express the evolving function of backlog in Q_i

$$Q_i(\tau) = \begin{cases} Q_i(t) & \text{when } \tau = t, \\ (Q_i(\tau-\xi) - \mu_i(\tau))^+ + \lambda_i(\tau) & \text{otherwise.} \end{cases} \tag{7}$$

where x^+ equals to x if x is positive, and equals to 0 otherwise. In this equation, $\mu_i(\tau)$ and $\lambda_i(\tau)$ are the service rate and arrival rate of Q_i in slot τ.

Given a park-and-charge station i, the service rate $\mu_i(\tau)$in a given fine-grained time slot τ is composed of two parts, the *charging service rate* and the *leaving service rate*, i.e., $\mu_i(\tau) = \mu_i^c(\tau) + \mu_i^l(\tau)$. The charging service rate $\mu_i^c(\tau)$

fulfills the charging demand of EV users, and is computed as the sum of generated electricity and purchased electricity without the sold electricity in a fine-grained slot τ:

$$\mu_i^c(\tau) = r_i(\tau) + E_{Gi}(\tau) - E_{iG}(\tau) \qquad \forall i, \tag{8}$$

which is nonnegative and bounded. The leaving service rate, denoted by $\mu_i^l(\tau)$, represents the charging demand canceled by EV users voluntarily, e.g., leaving the park-and-charge station i, during time slot τ. This rate is bounded but uncontrollable. For every EV user who canceled the remaining charging demand, she will receive a refund. For simplicity, we use $p_i^l(\tau)\mu_i^l(\tau)$ to denote the total refund to users during τ, where $p_i^l(\tau)$ is the average refund price.

The arrival rate for the charging demand queue of station i in fine-grained slot τ is computed as the charging demand of arriving EVs during this period, which can be obtained from EV users' demand response over charging price $p_i(t)$. We use $\mathcal{M}_i(\tau)$ to denote the set of EVs that can arrive at station i by the end of slot τ. By applying the quadratic pricing function in Equation (6), a charging station i can calculate the arrival rate of EV charging request during time slot τ as:

$$\lambda_i(\tau) = \sum_{j}^{j\in\mathcal{M}_i(\tau)} Pr_j^i(t)Cr_j,. \tag{9}$$

where $\tau \in [t, t+(F-1)\xi]$ and $Cr_j = (1 - SOC_j(t))E_j$. Summing up $\lambda_i(\tau)$, we can also get $\lambda_i(t) = \sum \lambda_i(\tau)$.

With the evolving function of Q_i on fine-grained time scale in Equation (7), we can get the evolving function on coarse-grained time scale. Because at the beginning of every time slot t, charging station i will drop $d_i(t)$ charging demand, the coarse-grained evolving function can be expressed as:

$$Q_i(t+T) = (Q_i(\tau) - \mu_i(\tau) - d_i(t))^+ + \lambda_i(\tau), \tag{10}$$

where $\tau = t+(F-1)\xi$. We see that the backlogs of charging demand queues reflects the delay experienced by EV users via Little's theorem [9]. To fulfill their charging demand within finite delay, the park-and-charge facilities must ensure stability on the queues of charging demand. To this end, we define that a system of park-and-charge facilities is *stable* if the following condition holds:

$$Q_{av} \triangleq \lim_{K\to\infty} \frac{1}{K} \sum_{k=0}^{K-1} \sum_{i=1}^{N} \mathbb{E}\{Q_i(kT)\} < \infty. \tag{11}$$

B. Problem Formulation

In this paper, we focus on maximizing the revenue of park-and-charge facilities. Given a charging station i, its income in a coarse-grained time slot $t = kT$ is composed of the charging expense paid by EV users who accept the price $p_i(t)$ and will arrive at station i by the end of t, and the income made by selling electricity back to the power grid. Its cost is the sum of the cost of electricity purchase from power grid, the refund to EV users who cancel their charging demand voluntarily (e.g., leaving the parking lot) and the penalty brought by station proportionally dropping some charging demand. Therefore, the revenue can be expressed as the difference between its income and cost:

$$\begin{aligned} Rev_i(t) = \; & p_i(t)\lambda_i(t) - p_{max}d_i(t) - p_i^l(t)\mu_i^l(t) \\ & + p_{iG}(t)E_{iG}(t) - p_{Gi}(t)E_{Gi}(t) \\ = \; & p_i(t)\lambda_i(t) - p_{max}d_i(t) - p_l\mu_i^l(t) \\ & + \sum_{\tau=t}^{t+(F-1)\xi} (p_{iG}(t)E_{iG}(\tau) - p_{Gi}(t)E_{Gi}(\tau)), \end{aligned}$$

where $p_{Gi}(t)$ and $p_{iG}(t)$ are the prices for charging stations to purchase and selling electricity from power grid.

We define that the system state ω includes electricity prices (p_{Gi}, p_{iG}), renewable energy profile (R_i), user-cancellation rate (μ_i^l), user-cancellation average refund price (p_i^l) and the status of EV users, and assume all these parameters in $\omega(t)$ are i.i.d. over every time slot. The revenue maximization problem (**REV-MAX**) for park-and-charge facilities is formulated as the following stochastic optimization model:

$$\begin{array}{rl} \max & Rev_{av} \triangleq \lim_{K\to\infty} \frac{1}{K} \sum_{k=0}^{K-1} \sum_{i=1}^{N} \mathbb{E}\{Rev_i(kT)\} \\ \text{over} & p_i(t), r_i(\tau), E_{iG}(\tau), E_{Gi}(\tau) \\ \text{subject to} & (1)(2)(3)(4)(5)(11) \\ & \text{for each } i,\ \tau \text{ and } t = kT. \end{array} \tag{12}$$

IV. GreenBroker: A Park-and-Charge Management System

We design the *GreenBroker* system. Its basic idea is to first transform the **REV-MAX** problem into a series of one-shot nonlinear optimization problems, and then decompose each one-shot problem into three subproblems, each of which can be solved by the station independently and efficiently.

A. Drift-Plus-Penalty Bound

We define a vector of ϵ-persistent virtual service queues $\mathbf{Z} = \{Z_1, Z_2, \ldots, Z_N\}$, one for each park-and-charge station i in the **REV-MAX** problem. This technique was first introduced for network utility maximization [9]. We have $Z_i(0) = 0$. The evolving function of virtual queues are:

$$Z_i(t+T) = \begin{cases} (Z_i(t) - \mu_i(t) - d_i(t) + \epsilon)^+, & \\ & \text{if } Q_i(t) > \mu_i(t) + d_i(t), \\ 0, & \text{if } Q_i(t) \le \mu_i(t) + d_i(t). \end{cases} \tag{13}$$

where ϵ is a positive constant that satisfies $\epsilon \in [0, \lambda_{max}^t]$. Denoting $\Phi(t) = \{\mathbf{Q}(t), \mathbf{Z}(t)\}$, we define a quadratic *Lyapunov function* $L(\mathbf{\Phi}(t))$ as a scalar measurement of the aggregated backlog of both actual queue Q_is and virtual queue Z_is:

$$L(\mathbf{\Phi}(t)) \triangleq \frac{1}{2} \sum_{i=1}^{N} (Q_i^2(t) + Z_i^2(t)). \tag{14}$$

This function represents the status of queue congestion in charging stations. To ensure the *stability* of the charging station system, we define the *T-slot Lyapunov drift function* $\Delta_T(\mathbf{\Phi}(t))$ as the expected difference of Lyapunov function.

$$\Delta_T(\mathbf{\Phi}(t)) \triangleq \mathbb{E}[L(\mathbf{\Phi}(t+T)) - L(\mathbf{\Phi}(t))|\mathbf{\Phi}(\mathbf{t})], \tag{15}$$

In addition, we define a *Lyapunov penalty function* $Pen(t)$:

$$Pen(t) \triangleq -\sum_{i=1}^{N} Rev_i(t). \tag{16}$$

We then propose the following theorem:

Theorem 1: Suppose $\omega(t)$ is i.i.d. over slots t. Assume that the quadratic Lyapunov function in Equation (14) satisfies $\mathbb{E}[L(\mathbf{\Phi}(0))] < \infty$. Let $V > 0$ and $t = kT$, where $k = 1, 2, \ldots$. Under all possible electricity pricing, generating, trading and dropping actions that satisfy the constraints in the **REV-MAX** problem, there exists a positive constant B_1 such that the Lyapunov drift-plus-penalty function satisfies:

$$\begin{aligned} & \Delta_T(\mathbf{\Phi}(t)) + V\mathbb{E}\{Pen_T(t)|\mathbf{\Phi}(t)\} \\ \le \; & B_1 + \theta_1(t) + \theta_2(t) + \theta_3(t), \end{aligned} \tag{17}$$

where

$$\theta_1(t) = \mathbb{E}\{\sum_{i=1}^{N} \lambda_i(t)\big(Q_i(t) - Vp_i(t)\big)|\mathbf{\Phi}(t)\}, \tag{18}$$

$$\theta_2(t) = \mathbb{E}\{\sum_{i=1}^{N} \sum_{\tau=t}^{t+(F-1)\xi} \Big(Vp_i^l(\tau)\mu_i^l(\tau) + Vp_{Gi}(t)E_{Gi}(\tau) - Vp_{iG(t)}E_{iG}(\tau) - (Q_i(t) + Z_i(t))\mu_i(\tau)\Big)|\mathbf{\Phi}(t)\}, \tag{19}$$

$$\theta_3(t) = \mathbb{E}\{\sum_{i=1}^{N}(V \cdot p_{max} - Q_i(t) - Z_i(t))d_i(t)|\mathbf{\Phi}(t)\}. \tag{20}$$

$$B_1 = N(\lambda_{max}^t)^2 + \frac{N}{2}(\mu_{max}^{t-c} + \mu_{max}^{t-l})^2 + \frac{N}{2}(\lambda_{max}^t + \mu_{max}^{t-c} + \mu_{max}^{t-l})^2 \tag{21}$$

B. Design Details of GreenBroker

Instead of maximizing the time average revenue of park-and-charge stations over all time slots, we propose to minimize $B_1 + \theta_1(t) + \theta_2(t) + \theta_3(t)$, the upper bound of the Lyapunov drift-plus-penalty function in Theorem 1. In this way, we transform the **REV-MAX** problem into a series of one-shot optimization problems $\mathbf{P_1}(t)$.

$$\begin{array}{lll} \mathbf{P_1}(t): & \text{min} & \theta_1(t) + \theta_2(t) + \theta_3(t) \\ & \text{over} & p_i(t), d_i(t), r_i(\tau), E_{iG}(\tau), E_{Gi}(\tau) \\ & \text{subject to} & (1)(2)(3)(4)(5) \\ & & \text{for each } i, \end{array} \tag{22}$$

where B_1 is omitted from the objective function since it is a positive constant. In $\mathbf{P_1}(t)$, we can find that $\theta_1(t)$ only contains electricity pricing variables $p_i(t)$, that $\theta_2(t)$ only contains electricity generating and trading variables $r_i(\tau)$, $E_{iG}(\tau)$ and $E_{Gi}(\tau)$, and that $\theta_3(t)$ only contains charging demand dropping variables $d_i(t)$. Thus we can further decompose problem $\mathbf{P_1}(t)$ into:

$$\begin{array}{lll} \mathbf{P_{price}}(t): & \text{min} & \theta_1(t) \\ & \text{over} & p_i(t) \\ & \text{subject to} & (1) \text{ for each } i, \end{array} \tag{23}$$

$$\begin{array}{lll} \mathbf{P_{trade}}(t): & \text{min} & \theta_2(t) \\ & \text{over} & r_i(\tau), E_{iG}(\tau), E_{Gi}(\tau) \\ & \text{subject to} & (2)(3)(4) \text{ for each } i, \end{array} \tag{24}$$

$$\begin{array}{lll} \mathbf{P_{drop}}(t): & \text{min} & \theta_3(t) \\ & \text{over} & d_i(t) \\ & \text{subject to} & (5) \text{ for each } i. \end{array} \tag{25}$$

In order to solve problem $\mathbf{P_{price}}(t)$ and $\mathbf{P_{drop}}(t)$, we only need that the charging station i solves two sub problems $\mathbf{P_{price}}(i,t)$ and $\mathbf{P_{drop}}(i,t)$. And to solve problem $\mathbf{P_{trade}}(t)$, we only need that the charging station i solves a sub problem $\mathbf{P_{trade}}(i,\tau)$ for each $\tau \in [t, t+(F-1)\xi]$. All these subproblems can be solved by a charging station independently. Therefore, we can propose, *GreenBroker*, an online distributed algorithm.

In *GreenBroker*, each charging station i independently makes online operation decisions, i.e., $p_i(t)$, $r_i(\tau)$, $E_{Gi}(\tau)$, $E_{iG}(\tau)$ and $d_i(t)$, only based on current queue backlog $Q_i(t)$, $Z_i(t)$, and current system state $\omega(t)$. The *GreenBroker* is online, fully distributed, and lightweight. Solving problem $\mathbf{P_{price}}(i,t)$ is essentially to find the minimal value of a cubic function of $p_i(t)$. And solving problem $\mathbf{P_{trade}}(i,\tau)$ is to solve a linear programming problem with three decision variables $r_i(\tau)$, $E_{Gi}(\tau)$ and $E_{iG}(\tau)$. In addition, the optimal solution to problem $\mathbf{P_{drop}^{ext}}(i,t)$ can be quickly achieved by Equation (26).

$$d_i(t) = \begin{cases} \lambda_{max}^t, & \text{if } Q_i(t) + Z_i(t) > V \cdot p_{max}, \\ 0, & \text{if } Q_i(t) + Z_i(t) \le V \cdot p_{max}. \end{cases} \tag{26}$$

C. Performance Analysis

Theorem 2: (*Revenue of GreenBroker*) Suppose $\omega(t)$ is i.i.d. over slots t and $\mathbb{E}[L(\mathbf{\Phi}(0))] < \infty$. Let Rev_{av}^{opt} denote the supremum time average revenue achievable by any operation strategy that meets the constraints in the **REV-MAX** problem and B_1 be the constant given in Theorem 1. The time-averaged revenue Rev_{av}^{GC} achieved by *GreenBroker* with a fixed parameter $\epsilon \in [0, \lambda_{max}^t]$ and a fixed parameter $V > 0$ satisfies the following bound:

$$Rev_{av}^{GC} \ge Rev_{av}^{opt} - \frac{B_1}{V}. \tag{27}$$

Theorem 2 indicates that in *GreenBroker* the time-averaged revenue of park-and-charge stations increases linearly as EV does. Furthermore, we analyze the worst-case delay provided by *GreenBroker* in terms of coarse-grained time slots. To this end, we first propose the following lemma:

Lemma 1: Suppose $\omega(t)$ is i.i.d. over slots t and the queue of charging request $Q_i(t)$ and the ϵ-persistent service queue $Z_i(t)$ evolve according to Equations (7)(10) and Equation (13), respectively. Assume EVs are charged in FIFO order, while the charging demand drop is performed with proportional dropping. If $Q_i(t) \le Q_i^{max}$ and $Z_i(t) \le Z_i^{max}$ are guaranteed for each coarse-grained time slot t, the worst-case delay of any non-dropped EV charging demand is:

$$W_i^{max} \triangleq \lceil \frac{Q_i^{max} + Z_i^{max}}{\epsilon} \rceil. \tag{28}$$

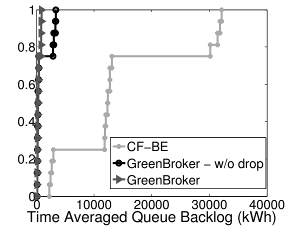
Based on this lemma, we then propose the following theorem on the worst-case delay of EV users in *GreenBroker*.

Theorem 3: (*Worst-Case Delay of GreenBroker*) Suppose $\omega(t)$ is i.i.d. over slots t. For the **REV-MAX** problem, running *GreenBroker* with a fixed parameter $\epsilon \in [0, \lambda_{max}^t]$ and a fixed parameter $V > 0$ guarantees that the worst-case delay of EV charging request at EV charging station i is:

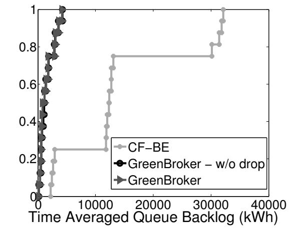
$$W_i^{max} = \lceil \frac{2V \cdot p_{max} + \lambda_{max}^t + \epsilon}{\epsilon} \rceil. \tag{29}$$

V. Numerical Simulation

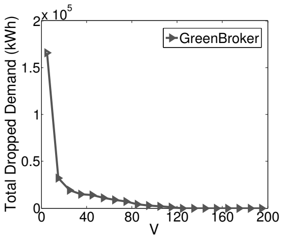
We perform numerical simulations to demonstrate the efficiency of *GreenBroker*. We set a coarse-grained time slot as one-hour, and a fine-grained time slot as 10-minute. We build a virtual traffic network with an area of $150 \times 150km^2$. 16 park-and-charge stations are deployed as a 4×4 grid, each of which has a maximal electricity purchasing and selling threshold of $200kWh$, a maximal EV charging service rate of $300kWh$ and a maximal EV charging request arrival rate of $1000kWh$ for every coarse-grained time slot. We randomly choose the hourly wind power generation capacity profile from 16 different locations in the United Sates [2] during a same 48-hour period, one for each charging station. We use hourly price data of 16 different places recorded by NYISO [1] as the price information provided to each charging station, and define a ratio of 0.4 for the sell back price. We define the price cap p_{max} as $60\$/kWh$. We also set the impact factors κ_p, κ_s and κ_d in Equation (6) as 0.1, 1 and 1, respectively. We assume each EV has the same specifications including a battery capacity of $40kWh$, a maximal driving range of 120 miles and a driving speed of $60mph$. After an EV arrives at a charging station, in every coarse-grained time slot before it is fully charged, the user has a probability randomly chosen between 0.1 and 0.4 to leave and get the refund.



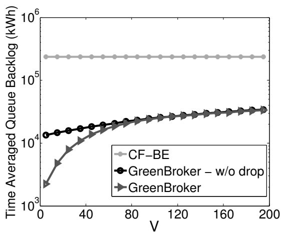
(a) CDF of Q^i_{av} when $V = 20$



(b) CDF of Q^i_{av} when $V = 100$



(c) d_{total} vs. V



(d) Q_{av} vs. V

Fig. 2: Light Traffic: Social Objectives.

Other than *GreenBroker*, we simulated another two strategies of charging stations. The first one is the *GreenBroker* without proportional demand drop, denoted as *GreenBroker-w/o drop*. The other one is a naive Closest-First Best-Effort (*CF-BE*) operation strategy. In this strategy, there is no communication channel between EV and charging stations. Each EV j selects the closest charging station. And charging stations adopt a best-effort strategy to serve the EV users.

We evaluate the performance of all three algorithms under two different traffic scenarios. In the **Light Traffic** scenario, 1000 EVs are uniformly distributed in the whole region. In the **Heavy Traffic** scenario, the number of EVs is 2000.

Figures 2(a)-(d) present the performance of all three algorithms in terms of backlog of charging demand queue in the light traffic case. Figure 2(a) and 2(b) show the CDF of time-averaged queue backlog Q^i_{av} across all 16 stations. No matter the V is small (i.e., 20) or large (i.e. ,100), *GreenBroker* can control queues of charging demand at all, outperforming *CF-BE* and *GreenBroker-w/o drop*. This is because when V is small, *GreenBroker* makes every station drop a large amount of charging request according to Equation (26) for guaranteeing the worst-delay. Figure 2(c) plots the total amount of dropped demand d_{total} of *GreenBroker*. We can see that the total dropped demand approaches to zero when $V = 100$. In Figure 2(d), we plot the time-averaged queue backlog Q_{av} of three algorithms. The performance of *CF-BE* is not affected by the parameter V, therefore its Q_{av} stays as a constant. For both versions of *GreenBroker*, their Q_{av}s increase as V does. While this increase in the no-dropping version is linear, the increase of Q_{av} for *GreenBroker* is faster when V is small. When V is large enough, both algorithms' queue backlog Q_{av} become the same and increases linearly. Even when V is large, the time-averaged queue backlog in *GreenBroker* is still smaller than that of *CF-BE*. These observations demonstrate the efficiency of *GreenBroker* in fulfilling the charging demand within finite delay.

Figure 3 shows the performance of *GreenBroker* and its no-dropping version on maximizing park-and-charge stations' revenue. We do not include the *CF-BE* strategy because it does not having any pricing strategy. The time-

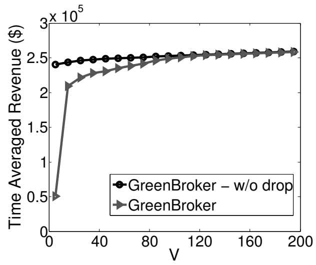


Fig. 3: Light Traffic: Rev_{av} vs. V.

averaged revenue Rev_{av} in both algorithms increase as V does. When V is small, the revenue of *GreenBroker* is much smaller than that of the no-dropping version. As V increases, however, the revenue of *GreenBroker* increases fast. When V is large enough, there will be zero charging demand dropped according to Equation (26), hence zero penalty cost. In this way, increasing V will have the same effect on increasing total revenue in both algorithms. Hence, *GreenBroker* is efficient in maximizing the revenue of charging stations. The other results are omitted due to the space limit. Readers may refer to [6] for details.

VI. Conclusion

We study the problem of maximizing the revenue of park-and-charge stations while guaranteeing the delay for EV users. We build a stochastic optimization model for this problem, and design *GreenBroker*, a park-and-charge management system which controls the arriving / charging rate of EV users by charging pricing, electricity generation and trading decisions. We analyze the theoretical bounds and evaluate the performance via trace-data simulation.

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